Using Machine Learning to Predict Student Success and Combat Inequity

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Welcome

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Academic Data Analytics

• Office of the Provost
• Culture of data-driven decision-making
  • Shape policy
  • Prioritize equity
  • Increase transparency
• Focus areas:
  • Predicting student success
  • Understanding student feedback
  • Visualizing complex data
  • Understanding student and faculty progression
Session
Roadmap

1. Project overview
2. Motivation
3. Our process
4. Early results and reflections
5. Discussion
Learning Goals

Understand applications of machine learning

Engage with interplay between machine learning and equity

Identify implementation opportunities at home institutions
Project Overview
Prediction Task

Which incoming students will not persist to their second term?

- Include all incoming first-time first-year students
- Predict before students matriculate
- Each year, use predictions to target early advising intervention
• Many varieties; today’s focus is **predictive analytics**

• Harnesses large amounts of **data** and **computing power**

• Searches for **relationships** between inputs and outputs

• Finds patterns **more complex** than human eyes and traditional methods can handle

• Not magical, but **powerful in the right situation**
Motivation
Central Challenge

Non-Retention
- Damaging to students and university
- Disproportionately impacts most vulnerable students

Timely Intervention
- Difficult to recover from early negative experiences
- Proactive interventions are more effective than reactive ones

Finite Resources
- Fewer advisors than students
- Must choose who receives a given intervention first
Central Challenge

Can we *predict which incoming students will not persist* to their second term?

*How early* can we make our predictions?

Non-Retention  Early Intervention  Finite Resources
• **Early advising** already in place
• **Mathematical model** already in use
  - Predicts **first-term GPA**
  - Traditional **linear regression**
  - **Unable** to predict second-term retention
  - A useful tool, but a **compromise**
• Not evaluated for **equity**
Promises

• Greater **predictive power**
• Better equipped for **challenging outcomes**
• Harnesses **bigger, messier data**

Concerns

• Will **human stakeholders** lose their voice?
• Might the algorithm be **biased or inequitable**?
• How much **transparency** will be offered?

**Machine Learning**
Our Process
Process Commitments

**PARTICIPATORY**
Engage meaningfully with a range of stakeholders

**TRANSPARENT**
Report honestly and accessibly on process and outcomes

**EQUITY-ORIENTED**
Apply lens throughout; demonstrably advance equity
Process Highlights

**Participatory**
- Partner closely with Undergraduate Education and Student Success
- Converse with other offices
- Reflect student body through diverse data sources

**Transparent**
- Report actively to UESS throughout
- Publicly disseminate methods and results
- Acknowledge strengths and limitations

**Equity-Oriented**
- With stakeholders, define equity standards
- Ground our work in existing scholarship
- Thoroughly vet model for equity and revise as necessary
Early Results & Reflections
Model Performance, 2021 Cohort

ADA Model
Potent. Vuln. Students

ADA Model
All Students

GPA Alternative
All Students

Random Lottery
All Students
ADA Model Out-Performs Alternatives

Non-Returners Identified

Student Cohort


* The 2021 cohort was hidden from the model during development to simulate an incoming cohort of students.
• Refine model **performance**
• Expand **equity analysis**; make any necessary **adjustments**
• **Deploy for incoming students** this year
• Begin **next predictive analytics project**
Reflections

- Confident that performance exceeds alternatives
- Room to continue improving
- Growing confidence in model equity
- Process was extremely successful
- Thoughtful approach, plus working in-house, enables responsible machine learning
- Ultimately, harnessed powerful new tools without undermining human stakeholders or potentially vulnerable students
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Open Discussion
Thank you!

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https://provost.uoregon.edu/analytics